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Are International Technology Gaps Growing or Shrinking in the Age of Globalization?

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1. Introduction

In 1956, Prime Minister Jawaharlal Nehru addressed fellow citizens at the site of the first Indian Institute of Technology (IIT) by suggesting that "…here…stands this fine monument of India, IIT, today representing India's urges, India's future in the making." The problem of development was for Nehru, as it was for policymakers and scholars, rooted in an economy's ability to close technology gaps. Then, as now, the stylized facts of the global distribution of technology divide the world into two broad groups. On the one hand, less developed economies are considered imitators, seeking to catch up by learning from the extant knowledge produced abroad. Meanwhile, advanced economies play the role of innovators, extending the frontier by producing new and better goods and services.

Although this anecdote of a technology 'race' between imitation and innovation remains with us today, contemporary researchers have significantly refined our understanding of its dynamics. Notwithstanding some formal modeling in which technology is assumed to be a global public good, many economists today recognize that technology varies from place to place, and that it is a vital determinant of differences in economic wellbeing. Endogenous growth theorists posit general equilibrium models in which technological inputs, such as human capital and research and development (R&D) drive an economy's overall growth rate (Aghion & Howitt 1992; Lucas 1986; Romer 1986). Economic geographers contend that there are significant transaction costs associated with the dissemination of new or nonroutine knowledge. These drive the locational concentration of economic activity, and they are a primary reason why investments in knowledge do not spill frictionlessly from place to place (Glaeser et al 1992; Storper & Venables 2004). In a complementary sense, economic historians and evolutionary economists argue that gaps persist because the diffusion of technology is far from automatic. Developing country firms expend great effort to adopt existing technologies, a process that calls for learning and adaptation, and which relies on institutions beyond the boundaries of the atomized firm, much like innovation itself (Lall 1992; Pavitt & Bell 1992; Viotti 2002).

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The theme of a race between latecomers' imitation and leaders' innovation also has new currency in the context of contemporary globalization. Many people in advanced economies are increasingly anxious that Nehru's hopes for his country have finally been realized, as latecomers like India and China expand their role in the global economy. Are these countries truly approaching world-class levels of technological advancement? Generalizing from these two oft-cited success stories, have information technology and global trade at last removed the hurdles that once obstructed latecomers from joining the club of advanced economies?

To be sure, the current period of globalization presents new possibilities for economies seeking to close technology gaps. Information technology, cheap transport, production fragmentation, rising foreign investment and intensified trade provide new or enhanced channels through which technology may be disseminated from advanced to developing economies (Blomström & Kokko 1998; Girma 2005; Keller 1997). But globalization's effect on technology gaps is ambiguous. Trade theory from Ricardo forward instructs that the expansion of trade drives greater specialization. For advanced economies this likely means more dedicated focus on goods, services and tasks that demand complex, non-routinized know-how. Economic geographers suggest that what makes these activities hard to codify also renders them less imitable, hence they are not easily contestable by low-cost producers (Leamer 2007; Storper 1997). In other words, the newly refined comparative advantage of advanced economies may stubbornly resist being offshored. Over the long run, advanced economies' deepening specialization may also set off circular and cumulative gains to technology. Perhaps it is building a foundation on which new, uncodified ideas are continually added, permitting today's technological leaders to perpetually outrun their imitators.

Despite the central importance to questions of development and globalization, we have of the little systematic evidence that we need to evaluate changes in international technology gaps. Technology is latent in the economy, embodied in products and services, making it hard to measure. We do have indications that countries vary in their total factor productivity (TFP), and that these differences are related to economic growth (Easterly & Levine 2001; Hall & Jones 1999; Klenow & Rodriguez-Clare 1997a). However, there is no agreed upon way of evaluating technology's contribution to TFP (Prescott 1997). We also know that countries differ in their innovative effort. But R&D expenditures and patent counts are partial measures at best. They fail to capture technological efforts in the form of imitation and adaptation that dwarf innovative effort in advanced economies (Jovanovic 1995), and are plausibly much larger among the less sophisticated.

In this paper I introduce a novel measure of technology, *TECH*, and use it to investigate the changing shape of international technology gaps. *TECH* evaluates an economy's overall technology level based on the products it exports, as function of three components. First, each product is assigned an 'implied sophistication' score, based on the revealed comparative advantage-weighted income level of its exporters, following Hausmann et al (2007). A product's implied sophistication will increase as high-income economies become progressively more specialized in its export. Second, following recent evidence that highlights the importance of intra-product differentiation (Hummels & Klenow 2002; Schott 2004), I assign a relative quality level to each economy's export of a good, using unit prices to compare it to its direct competitors. Third, the product of these two methods is combined with the share that each good occupies in each country's total exports, to arrive at the overall measure of an economy's technological sophistication, *TECH*.

I analyze annual changes in as many as 141 countries' levels of technological sophistication over the recent period of globalization, 1972-2001, and ask three main questions. First, have international technology gaps grown or shrunk? Second, what are the prospects for intradistributional mobility over the period studied: are economies 'stuck' in the relative positions in which they began, or do they make pronounced leaps forward and back? Third, is there evidence that economies that manage to leap forward do so for common reasons, in terms of changes in quality, implied productivity, and new product introductions?

My findings can be easily summarized. First, patterns of international technology gaps are complex, and irreducible to simple conclusion of convergence of divergence. However, technology's leading edge has expanded faster than low and moderately sophisticated economies have grown, consistent with an overall increase in the gap between technological haves and have-nots. Second, country technological positions are roughly stable over time. Most economies did not leap from one broad level of sophistication to another between 1972 and 2001. Moreover, it is the most sophisticated economies that most significantly upgraded the sophistication of their exports over the period studied. Third, the decomposition of country-group contributions to changes in *TECH* reveals that there are meaningful groups of countries that have upgraded in similar ways. Initial leaders grew primarily by consistent export of the same goods, but increasing the levels of quality and implied productivity, and with more dedicated focus. Meanwhile, less developed economies upgraded their TECH levels primarily by adding new and more sophisticated goods that they did not produce in earlier periods.

This paper proceeds as follows. In the next section I briefly review theories that relate technology and economic growth, and describe empirical approaches that researchers take to measure economy-wide technology levels. In Section 3 I outline my empirical specification of *TECH*, and describe the data used. Section 4 presents empirical results. I conclude in Section 5.

2. Growth and Technology

Technologies are rules and ideas that direct the way goods are created. They are codified in formal blueprints or tacitly held by individuals alone or in groups. Despite what we know from history - that technology is scarce, prized and competed for - orthodox economic models assume it is universally and freely available. Solow's (1956) workhorse neoclassical growth model supposes that only differences in physical capital accumulation explain the wealth of some countries and the poverty of others. Technological progress is vital in this model as a driver of the overall growth rate, but it is assumed that new techniques are instantly available to everyone.

Growth rates are inversely related to initial income, creating welfare effects as follows. Poor countries are capital-scarce, and the addition of capital provides these economies with a relatively greater growth stimulus than to the rich, because of decreasing returns. Poor countries thus grow faster than capital-abundant, wealthy economies. In the long run, rich and poor countries' per capita GDP growth rates converge, though this convergence does not necessarily lead to international equality in per capita incomes.

The predictions of the Solow model are odds with empirics. Not only is there little evidence of absolute income convergence, countries appear to be clustering into distinct clubs based not on initial income, but on the basis of institutional and other factors (Chatterji 1992; Quah 1992). Contrary to the model's predictions, capital is not flowing rapidly towards poor economies to seize upon higher rates of return (Lucas 1990), while rates of return in the U.S. have remained high for a century (King & Rebelo 1993). Furthermore, additions to the stock of capital and labor contribute only a fraction – as little as 10% in some rigorous analyses - of measured growth in output (Klenow & Rodriguez-Clare 1997b).[2] Total factor productivity (TFP) accounts for the residual, but TFP remains an exogenously determined black box. Most observers consider that technology accounts for some significant proportion of TFP, but we lack an accepted method for decomposing TFP, or even an accepted theory of its constituents (Prescott 1997). Moreover, after controlling for differences in capital intensity and educational attainment, TFP's contribution to growth still varies across countries (Hall & Jones 1999; Klenow & Rodriguez-Clare 1997a). Assuming a global technology pool, Solow's model cannot account for why some economies remain more productive than others after considering these factors.

'New,' or 'endogenous' growth models address some of these issues by rooting technological change or human capital accumulation in agents' profit-seeking decisions. According to these models, economies grow as firms seek gains through technological improvement or by increasing the stock of human capital. They drive technological change by investing in R&D (Aghion & Howitt 1992), and also by adopting and adapting existing technologies that are new to the organization (Jovanovic 1995). Agents also spur technological change through training and education (Lucas 1986; Romer 1986), and it can emerge from learning-by-doing (Arrow 1962). Technological advancements produced through these various efforts can diffuse between firms, across cities, regions and nations. Yet these spillovers cannot be frictionless otherwise there would be no incentive to invest in technology.

While differing in methods from general equilibrium-oriented endogenous growth theorists, economists taking historical and evolutionary perspectives on growth have long studied the obstacles that constrain the spread of technologies. The latter have demonstrated that technological adoption demands effort. Users of a technology often require specific human capital to make sense of it. Adoption consumes resources, as firms must license new technologies, and local adaptation may be required (Lall 1992). Moreover, learning, adaptation and innovation typically proceed from inter-organizational interactions that are bound up in shared conventions regarding trust, time horizons, and rationality (Lundvall et al 2002). These processes have a tacit dimension that encumbers the dissemination of ideas, and creates distinctive evolutionary trajectories of technological development within spatial, social, political and sectoral boundaries (Malerba 2002; Nelson 1993; Saxenian 1996; Storper 1997; Viotti 2002). Frictions in technology diffusion thereby open the door to variation in sophistication within particular industries, and in aggregate between regional and national economies.

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[2] By some estimates the addition of human capital to measures of capital accumulation can raise this fraction to as high as 80% Mankiw NG, Romer D, D.N. W. 1992. A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics* 107:407-37

In turn these technology gaps explain persistent international income differences.

Globalization has likely altered the pace at which technologies are spread. Advances in communication technologies over the last decades of the 20th century make it easier to share ideas, and they permit the formation of new kinds of social links across space. Deepening economic integration, in the form of growing impact of FDI and trade may also help to disseminate technologies. Under certain conditions, local agents accumulate new ideas and become more productive when foreign multinationals enter their markets (Blomström & Kokko 1998; Borensztein et al 1998; Xu 2000). Firms may also learn by importing and exporting (Keller 2002; Rivera-Batiz & Romer 1991). Hence, one likely force affecting the pace of diffusion is a dissemination effect, whereby communication technologies, trade, investment and cheap transportation hasten technological, and hence economic convergence.

However, these forces do not equally affect all technologies. Tacit ideas, meaning those to which we can apply Polanyi's aphorism: "we know more than we can tell" (Polanyi 1967), are not necessarily easier to exchange now than before. The City of London, Silicon Valley and other agglomerations premised on the circulation of nonroutine, tacit know how have not declined, though these locales have shed some activities and created new ones. Regional specialization is not on the wane in the 'internet age' (Leamer & Storper 2001; Scott & Storper 2003), even while cycles of knowledge creation and destruction have been accelerated (Lundvall & Nielsen 1999).

Increasing integration and technological change together plausibly induce a deepening of the division of labor in which advanced economies increasingly focus on nonroutine tasks, while certain kinds of routine production are offshored to developing countries (Autor et al 2003; Grossman & Rossi-Hansberg 2006). In terms of technological diffusion, this means that technologies subject to codification are likely to diffuse much more rapidly than before through the channels described above, while tasks that require complex and less systematic technologies remain bound in agglomerations inside advanced economies. The rewards from specialization in high-sophistication goods and services may be such that advanced economies outrun the pace of imitation in developing economies. The deepening global division of labor may provide self-perpetuating technological advantages to today's winners that reinforce existing technology gaps.

We need better empirics on technology to understand these issues. Technology measurement lags behind theory in part because technology is latent in the economy, embodied in products and tasks. Researchers have taken three main approaches to measuring technological differences. The first measures inputs and outputs into innovation. The second conflates TFP with technology. The third approach starts from the bottom up, gauging first the sophistication of individual products or industries and aggregating to the economy-wide level.

Inputs into innovation include expenditures on research and development (R&D) or dedicated human capital. Outputs include patents, bibliometrics, and counts of new product introductions. Each has strengths and weaknesses as indicators of innovation that have been widely discussed (Godin 2005; Griliches 1990; Pavitt 1984). But innovation and technology should not be conflated. By some estimates, R&D accounts for at most 0.5% of U.S. productivity growth (Comin 2004), while firms in advanced economies spend 20 to 30 times more on adoption than invention (Jovanovic 1995). Both of these estimates likely underemphasize the relative importance of adoption and adaptation in less developed countries where there is less innovation and scant formal R&D.

TFP measurement is straightforward, it makes use of widely available statistics, and flows directly from the neoclassical model. As discussed above however, TFP is also an undifferentiated amalgam of technological sophistication and other forces (Hulten 2000). TFP's actual contribution to output may also be understated since technological changes likely induce further capital accumulation (Barro & Sala-i-Martin 1995). Measures of capital accumulation therefore conceal technological change. Moreover, TFP's construction from aggregate price deflators may provide inaccurate results, since it ignores international variation in relative factor costs (Harrigan 1997).

Bottom-up approaches start by classifying individual products or industries according to their embodied technological sophistication. Product-level analyses provide needed granularity since industries are technologically variegated. Classifying an entire industry as 'high-technology' may conceal many routine, low-technology products. Linking productivity to individual goods also helps to clarify TFP's black box. The central challenge with this approach is deciding on an effective and efficient manner by which to assign technology levels to goods. Economists commonly use R&D intensity to rank goods. Even if this were a generally sound approach, R&D figures are rarely systematically available for individual products.

A recent paper by Hausmann, Rodrik and Hwang (2007) addresses this issue by using widely available trade and income data to classify products on the basis of the average income level of their exporters, and then aggregates up to the national level.[3] Their index is relatively easy to construct, and uses detailed, disaggregated data. Nonetheless, exporters are increasingly specialized not simply in particular types of goods, but vertically differentiated within goods themselves on the basis of quality and other factors (Hummels & Klenow 2002; Schott 2004). Both Italy and China produce broadly analogous silk shirts, for example. But Italy's display higher craftsmanship, are more closely keyed to rapidly changing fashions, and involve more sophisticated branding. Xu (2007) demonstrates that the Hausmann et al (2007) measure significantly overstates China's recent increase in sophistication as compared to his approach that also considers relative price differences. Ideally then, we need a measure that describes technology levels not only on the basis of the type of products an economy exports, but also the quality or sophistication of these goods relative to those of competing producers.

3. Empirical Framework

3a. Construction of TECH

My *TECH* index builds on several approaches that describe the sophistication of economies by evaluating traded products. I make three main contributions. First, I refine Xu's (2007) use of unit prices to capture an additional technological dynamic by accounting for both extensive (between-products) and intensive (within-products) margins of technological upgrading. Second, I adapt the measure in Hausmann et al (2007) to account for changes in the sophistication of products themselves over time. Third, this permits me to build *TECH* using a significantly longer time-series, and hence to investigate long-term dynamics in the distribution.

[3] Lall, Weiss and Zhang (2005) follow a similar course, but the authors use a slightly different method, with more aggregated data.

TECH is a function of three product-level elements:

(1) the implied productivity of the goods an economy exports (***p***),
(2) the quality of those exports relative to those of direct competitors (***q***),
(3) the value shares of each good in an economy's overall export basket (***x***).

Let nations, indexed by *n*, produce goods *g* at time *t*. Hence,

$$TECH_{nt} = \sum_g p_g q_{ng} x_{ng} \tag{1}$$

To build an identity for the implied productivity associated with an individual good, I calculate the average income of its exporters. Specifically, following Hausmann et al (2007), ***p*** (or *PRODY*) is a weighted-average of exporters' per capita GDP, where the weight is each exporter's revealed comparative advantage in the good being evaluated. My measure of implied productivity varies by product and year, but not by country. Hence,

$$p_g = \sum_n \left(\frac{x_{ng}}{\sum_n x_{ng}} \right) Y_n \tag{2}$$

where Y_{nt} indicates a nation's real per capita GDP. The numerator of the weight x_{ng} describes the degree of an economy's specialization in product *g*. Its denominator $\sum_n x_{ng}$ aggregates each exporter's value shares in product *g*. The procedure of weighting incomes by revealed comparative advantage is grounded in Ricardian theory that predicts the specialization patterns of an economy as a function of the goods it can produce most productively. Hence, we should expect rich countries to be highly specialized in sophisticated products, while poor economies specialize in unsophisticated goods. Revealed comparative advantage, since it is a relative measure, is also useful since it levels the playing field across countries of varying size.

To describe each exporter's position on a product quality ladder I construct an index of relative unit prices for each good. I consider that differences in importers' unit prices of a given product signal differences in quality levels. Following Xu (2007), I compare an economy's unit price to the unit prices of other countries' varieties, weighting the importance of prices on the basis of market share. If ***s*** is an economy's market share for good *g*, and ***u*** is its exporter's unit price, the relative price ***q*** of its variety is given as follows:

$$q_{ng} = \frac{u_{ng}}{\sum_n (s_{ng} u_{ng})} \tag{3}$$

A ***q*** score above 1 indicates that an exporters' variety occupies a favorable position on a quality ladder, while scores below 1 denote substandard quality.

The sum of the product of ***q***, ***p*** and ***x*** across all goods in an economy's export basket produces a country-level *TECH* score in a given year. The product of ***q*** and ***p*** creates a country- and product-specific value that reflects both the average sophistication of the good across all exporters, and the particular exporter's quality ladder position for this good. The product of these terms and ***x*** weights each product's sophistication score according to the relative intensity with which it is exported. Overall then, *TECH* evaluates the overall level of technological sophistication associated with a particular economy's exports.

3b. Data Description

I build annual *TECH* scores for 115 to 141 countries over the period 1972-2001, using data from two main sources. Income data, in the form of Chain-series per capita GDP, comes from Penn World Table (PWT), version 6.2 (Heston et al 2006). I use records of U.S. imports between 1972 and 2001 for product-level trade information. The U.S. Census Bureau records import information, which is compiled as part of a National Bureau of Economic Research (NBER) project. Feenstra, Romalis and Schott (2002) provides detailed documentation of the data. The database contains complete records of merchandise imports into the U.S. from 1972 to 2001. Each record describes the import into the U.S. of a single type of manufactured or natural resource product from a particular economy in a given year. Imports of services are excluded. From 1972 to 1988, products are primarily identified using the 7-digit Tariff Schedule for The United States, Annotated (TSUSA) number. Goods are identified using 10-digit Harmonized System (HS) codes from 1989 to 2001. As well as dollar denominated customs values for each instance of importing, the Census Bureau tracks quantities, units, country of origin, Standard International Trade Classification (SITC) rev.2 4-digit code, and other information. For inter-temporal comparability as well as concordance with GDP figures, I adjust nominal U.S. dollar customs values to base-year 2000 U.S. dollars, using Consumer Price Index (CPI) data from the U.S. Bureau of Labor Statistics (Bureau of Labor Statistics 2007).

To arrive at each good's unit price (*u*) in equation 3, I divide an import's customs value by the quantity of units imported.[4] This step demands the fine-grained detail provided by 7- and 10-digit product codes, since I derive ***q*** by comparing the prices of goods that are presumed to competitors. By contrast, aggregate sector- or industry-level classifications contain products that do not closely resemble each other. The comparison of unit prices of these dissimilar goods would create an uninterpretable relative price index. Nonetheless, the initial distribution of ***q*** remains implausibly wide, even at 7- and 10-digit levels.

Inaccuracies in record keeping may explain outliers in the distribution. An exploratory study finds significant error in U.S. import unit prices (General Accounting Office 1995). Implausible unit values could be the result of data entry errors, overly broad product classifications and other problems (ibid). I take several steps to minimize these errors, since they cannot be corrected *ex post*.[5] Because 90% of the values of the

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[4] Exporters may have multiple instances of exports of a product in a particular year. Of the 5,213,708 total records, 9% (463,761) are multiple country/product/year observations. Fortunately, multiples are in consistent unit types (for example: pounds or dozens) at the TSUSA or HS level. Hence, I collapse these instances into one observation per country/product/year, where the final unit price is a value-share weighted sum

[5] Scholars doing related work have undertaken several strategies to address this problem. Khandelwal (2007) deletes all import instances with a value below $10,000 or quantity of 1, and also eliminates observations with unit prices below the 5th and above the 95th percentile within 5-digit Standard International Trade Classification (SITC) 'sectors.' However, 5-digit SITC sectors contain varied products,

quality index are between the fairly reasonable bounds of 0.1 and 8.2 (the highest and lowest priced goods thereby differ by a factor of 82), I adjust only outliers that exert undue influence on country-level *TECH* scores.[6] I set unit prices of country/product pairs whose quality scores are below the 1st and above the 99th percentile to the average unit price among all other exporters of the product. The distorting effect of these outliers is then eliminated, since the exporter's $\boldsymbol{q}$ value for the product becomes equal to 1.[7] This method is relatively nondestructive, preserving the general effect of unit prices while making the least severe assumptions. I also set all $\boldsymbol{q}$ values for natural resource goods to 1, thereby ensuring that these goods' product scores are unaffected by quality differences.[8] Variability in international prices for natural resource imports should largely reflect comparative cost differences that are unrelated to technology. Initial and adjusted distributions of relative prices are shown in Table A2 of the data appendix.

My measure diverges from the index proposed by Hausmann et al (2007) in additional ways. I recalculate a good's revealed sophistication ($\boldsymbol{p}$) each year, using annual data on export shares and income, since the relatively long time period from which I construct *TECH* means that time-invariant product scores are inappropriate.[9] I expect a good's level of sophistication to change over three decades, as products are rendered more complex, or are standardized. However, a product's score can fluctuate from year to year in ways that can reflect composition effects rather than technological shifts. To minimize these non-technological effects, I smooth $\boldsymbol{p}$ scores using a 5-year moving average.[10][11]

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and as such it is too aggregated a level at which to make price comparisons. Moreover, we have no evidence that small-value or low-quantity imports are those records most likely to contain errors. Xu (2007) drops all observations below the 1st and above the 99th percentile within each product's Q distribution. To further reduce the effects of outliers, he adjusts Q by raising it to the power of $\theta = 0.2$, partly as a result of comparison with country-level R&D intensities, though the exponent remains somewhat arbitrary. $\theta = 0.2$ indicates very low confidence in the quality of unit prices, so much so that it nearly eliminates the impact of quality differences entirely.

6 The true ceiling for any given product is likely to be smaller than a comparison of the highest to the lowest $\boldsymbol{q}$ scores. This is because a given pair of low and high scores need not correspond to the same good.

7 A very small number of unusually high, and temporally inconsistent *TECH* scores remain. I find that these outliers are undiversified exporters with one unusually high $\boldsymbol{q}$ score that pushes *TECH* to an unlikely level. I resolve this issue by investigating the outlier country's history of exporting the good whose $\boldsymbol{q}$ results in their high *TECH* score. I find that most outlier economies have no history of exporting the product in other years. I adjust its unit price to the average of remaining exporters of this good if the country has either never exported this good in other years, or has done so within a much more moderate range of $\boldsymbol{q}$ scores.

8 I define natural resources as goods with SITC rev.2 codes 0-4, and 9, not including 95

9 Hausmann et al (2007) create a singular, static PRODY score for each good as a 3 year average of the years 1999-2001, and apply this score backwards over 1992-2003..

10 After experimenting with different formulae for smoothing, I arrived at the (1 1 3) approach, using the following formula: (1/5)*[x(t-1) + 1*x(t) + x(t+1) + x(t+2) + x(t+3)]; x(t)=$\boldsymbol{p}$. This method struck the best balance between capturing trends in the $\boldsymbol{p}$ scores, while eliminating implausible variation.

11 I extensively correct the original U.S. import data series in order to ensure intertemporal comparability within individual products, within each series, 1972-1988 and 1989-2001. As noted in Feenstra et al (2002), the code used to identify a particular good may change from year to year. The same code is also occasionally used to identify different goods in different years. I also discovered that the original data includes what appear to be a single good coded differently even within the same year. Acetone, for example, appears as both TSUSA #4276000 and #4066400 in 1988. I took several steps to resolve these issues. Primarily, I match products across time using their detailed alphabetic descriptions, after removing punctuation and other sources of error. Products were also matched according to their initial product codes,

Unlike Hausmann et al (2007), I also maximize the number of countries in each year instead of using a balanced panel.[12] I do so for two main reasons. First, U.S. import data differs from the United Nations Commodity Trade Statistics Database (COMTRADE) used by Hausmann et al (2007) in that it does not depend on voluntary reporting from exporters. Hence, the increasing group of countries reflects not declining nonreporting but actual growth in the diversity of sources of U.S. imports. Second, *TECH* results do not appreciably differ when built from the unbalanced panel. Hence, my data models exports from 115 countries for much of the period, expanding to 141 by 2001.

My construction of *TECH* relies on the presumptions that exports reveal an economy's overall technological structure, and also that exports to the U.S. mirror economies' general patterns of world exports. Exports are widely held to be a reasonable indicator of the leading edge of domestic technological capabilities, since exports signal an economy's ability to competitively produce for the world market, while untraded or trade-protected goods may persist despite being of poor quality. Exports are a noisy, albeit superior signal of technology sophistication (Khan 2006).[13]

At least two main forces support the relationship between U.S. exports and world trade patterns: the openness of the U.S. economy, as well as the attractiveness of its large market (Schott 2006). On the other hand, bilateral trade volumes decline with distance for several reasons (Anderson & van Wincoop 2004; McCallum 1995; Wei 1996), which might render the analogy less valid. To investigate this further, I build an additional version of the index using trade data the World Trade Flows (WTF) dataset.[14] The two indices have a correlation coefficient of 0.86, and scatterplots at various cross-sections, shown in Figure A2 in the data appendix, generally support the use of U.S. imports as a proxy for world trade patterns more generally.

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with non-matches manually identified and resolved using external sources. Products were assigned new, intertemporal consistent codes on the basis of these matches. Stata do-files to perform these actions are available upon request.

[12] All exporting countries are included except OPEC nations. Because of their unusually high GDP as a result of petroleum exports, the OPEC countries apply undue leverage on the *TECH* distribution. Countries are listed in Table A1 of the data appendix.

[13] One important element of the noise, both for export data generally, and specifically for the *TECH* index, is the rise of fragmented production processes documented in papers such as Hummels D, Ishii J, Yi KM. 2001. The nature and growth of vertical specialization in world trade. *Journal of International Economics* 54:75-96. *TECH* cannot account for the fact that an individual product imported into the U.S. may have been produced in a variety of economies, each performing different elements of the production process that reflect their diverse levels of sophistication. My index will assign the sophistication associated with this good to its 'final' producer who exports the good to the U.S. (who may not be the actual final producer, in that a firm in the U.S. may add additional value to the good before exporting it elsewhere. The detailed product level data used to build *TECH* mitigates some of this issue: Imported parts will be as precisely identified as possible as being parts, rather than being confused with final, fully assembled goods which might occur at higher aggregation. However, we cannot know which other producing countries have also contributed to the product that is recorded as a U.S. import.

[14] WTF records bilateral trade flows between over 100 countries from 1962 to 2000 at the Standard International Trade Classification (SITC), revision 2, 4-digit level. This data measures world trade flows as opposed to U.S. imports, but its products are classified at a yet more aggregated level (for full documentation, see Feenstra RC, Lipsey RE, Deng H, Ma AC, Mo H. 2005. World Trade Flows: 1962-2000. *NBER Working Paper* 11040). I therefore construct country-level scores without quality adjustments. Such a quality adjustment is impossible in any case, since WTF contains price and quantity data for only selected records, and starting only in 1984.

Table 1 displays top and bottom 5 *TECH* scores in 1972 and 2001. Leaders in 1972 are all high-income Western European economies. The least sophisticated economies include poor South Asian and African nations. This pattern repeats in 2001, with Ireland being added to the top 5. Those at the bottom are all African except Tajikistan.

Table 1. Top and bottom countries in TECH, 1972 and 2001

1972	2001
Top 5	Top 5
Switzerland	Denmark
Sweden	Austria
Austria	Switzerland
Germany	Ireland
Denmark	Sweden
Bottom 5	Bottom 5
Nepal	Liberia
Sudan	Sudan
Bangladesh	Tajikistan
Mongolia	Chad
Malawi	Malawi

As expected, there is a strong relationship between TECH and per capita GDP.[15] As Hausmann et al (2007) note however, GDP does not lead mechanically to a given TECH score, despite their interrelationship by construction. Independence between the two is even clearer in my index, given the distinct impact of unit prices. The effect of unit prices likely strengthens the connection between GDP and TECH however, since rich countries are those that export goods with high relative unit prices (Schott 2004).

Table 2. Correlation between *TECH* and other technological measures

	1990	2000
	TECH	*TECH*
Higher Education[16]	0.72	0.64
Patent	0.70	0.58
Infrastructure	0.74	0.74
TFP[17]	0.66	-

[15] TECH and PCGDP have an average annual correlation coefficient around 0.84.

[16] Education, patent and infrastructure measures are taken from Archibugi and Coco (2004), where they are documented in more detail. Briefly, 'Education' measures the share of students enrolled in tertiary study of social and physical science in the comparable age group. 'Patent' describes the mean U.S.P.T.O.-filed patents per million inhabitants. 'Infrastructure' is an unweighted average of population weighted measures of the penetration of internet, landline and cellular and electricity.

[17] The measure of total factor productivity used comes from Hall RE, Jones CI. 1999. Why Do Some Countries Produce So Much More Output per Worker than Others? *Technology* 83. The authors disaggregate output per worker into measures of capital intensity, human capital per worker and productivity for the year 1988. Hence, the correlation in Table 2 is between *TECH* and TFP for 1988, for the 117 economies in both data sets. Each economy's TFP is calculated as a ratio of the U.S. value.

Table 2 demonstrates TECH's association with 3 different measures of 'technological capability' outlined in Archibugi and Coco (2004), as well as a measure of TFP. Interestingly, while coefficients remain similar across time for measures of educational attainment and technological infrastructure, the association with patents weakens in 2000. Scatterplots of the relationship between *TECH* and the measure of patents mostly confirms the ineffectiveness of the latter as a meaningful measure of technological advancement across countries at a diverse range of incomes. Simply, only advanced economies patent in any significant quantity in 1990 as well as in 2000. *TECH*'s somewhat diminished correlation with the measure of tertiary science and engineering education also points to an anomaly, as a handful of very small economies whose *TECH* scores reflect their lack of diversification bias the correlation.[18] The last row in the table indicates a moderately high correlation between TFP and *TECH* in 1988.

4. Empirical Results

4a. Technology Gaps Have Not Diminished Among U.S. Trading Partners

Technology's geography is strikingly uneven. Of the 141 countries for which I build *TECH* scores in 2001, only 53 are above the mean level of technology. These 53 nations contribute 66% of the total *TECH* among all U.S. trading partners, yet they consist of only 21% of the world's population.[19] Technological differences are in fact starker than this snapshot reveals. The 15 most sophisticated economies in 2001 have a 25% share of the globe's total technology while representing only 5% of its population.

This gap between advanced and unsophisticated exporters is not a recent development. Table 3 describes the *TECH* distribution at several cross-sections. Mean sophistication has steadily increased from 1972 to 2001, consistent with generalized technological progress. That median scores are consistently below the mean confirms that most economies start and remain less sophisticated than the world average. The standard deviation of the distribution has increased, suggesting a growing spread in the range of *TECH* values. The fourth and fifth rows of the table display averages of the top and bottom 5 economies' *TECH* scores. While sophistication levels of the leading countries nearly doubles from 1972 to 2001, scores of the least advanced economies remain roughly stagnant. Ratios of the 5 highest to 5 lowest *TECH* scores show that the most sophisticated economies are 13 times as advanced as those at the bottom in 1972, but they become 25 times as advanced by the end of the period. Hence, the gap between these least and most advanced economies grows by a factor of 1.88 over the 30-year period. Interestingly, most of this change occurs in the 1990s.[20] Together, this evidence suggests that technological differences as measured by *TECH* are substantial, and they have grown.

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[18] See Figures B1-B3 in the appendix for the relevant plots

[19] This considers the 141 countries in the *TECH* index to be the world, and excludes the U.S., which does not import to itself.

[20] The year 2001 is not an outlier: the large increase in the gap between the tails of the distribution starts in 1991, and progresses through the decade. The average annual ratio between 1991 and 2001 is 21. The explanation appears to be an absolute decline of a number of African and Asian economies, combined with superior growth among the world's technological leaders. Moreover, the gap is not simply an artifact of a few poorly performing economies. The gap grows by a factor of 1.75 when we compare top and bottom 10 economies between 1972 and 2001, and by a factor of 1.4 for the top and bottom 20.

This suggestion of a widening gap between advanced and unsophisticated economies accords with evidence from the distribution of per capita incomes. However, the growing gap between the richest and poorest countries is significantly greater, almost doubling from 33 to 64 over the study period. The dynamics of the distribution of global sophistication broadly parallel, but are more constrained than that of income.[21]

Table 3. Indicators of Catch-up in Technological Sophistication, 1972-2001

	1972	1980	1990	2001
Mean	5,783.57	7,139.90	8,705.64	10,772.80
Median	4,513.60	5,663.50	6,266.00	8,163.30
Standard Deviation	4,177.76	4,939.10	6,513.90	7,729.33
Most Sophisticated*	17,068.77	20,660.98	26,627.01	32,127.92
Least Sophisticated*	1,280.62	1,555.22	1,673.58	1,281.00
Ratio of highest to lowest*	13.3	13.3	15.9	25.08
Coefficient of variation	0.72	0.69	0.75	0.72
Gini coefficient	0.38	0.36	0.39	0.39

*Average of top and bottom 5 observations

The final rows in Table 3 apply common metrics of statistical dispersion to *TECH*: the coefficient of variation and the Gini coefficient. *TECH*'s coefficient of variation will equal zero if all economies share the same level of technological sophistication, while higher values indicate greater spread among country technology levels. Gini coefficients range between 0 and 1. A value of zero means that countries share equally in the total *TECH* available in the world. *TECH* scores maintain a consistent coefficient of variation, ranging from 0.69 to 0.75. The Gini coefficient for *TECH* is similarly invariant. These 'dimensionless' indices suggest that the scale of gaps between advanced and less sophisticated economies remain in 2001 as they began in 1972.

The results in Table 3 therefore provide contradictory-seeming evidence on the evolution of technology gaps. Increases over time in the standard deviation and the ratio of the most to the least sophisticated economies suggest growing gaps, at least between the tails of the population of countries.[22] By contrast, the Gini and coefficient of variation point to relative stability in the overall spread of *TECH*.

These measures alone fail to capture the complexity of changing technology gaps, since very different distributions can share the same descriptive statistics and measures of inequality. The Gaussian kernel-smoothed density plot in Figure 1 provides a more multidimensional representation of *TECH*'s morphology between 1972 and 2001.[23] This

[21] This may be partly by construction since PRODY scores are weighted averages of income levels. However, the independent impact from relative prices (*Q*) ensures that this difference is not mechanical.

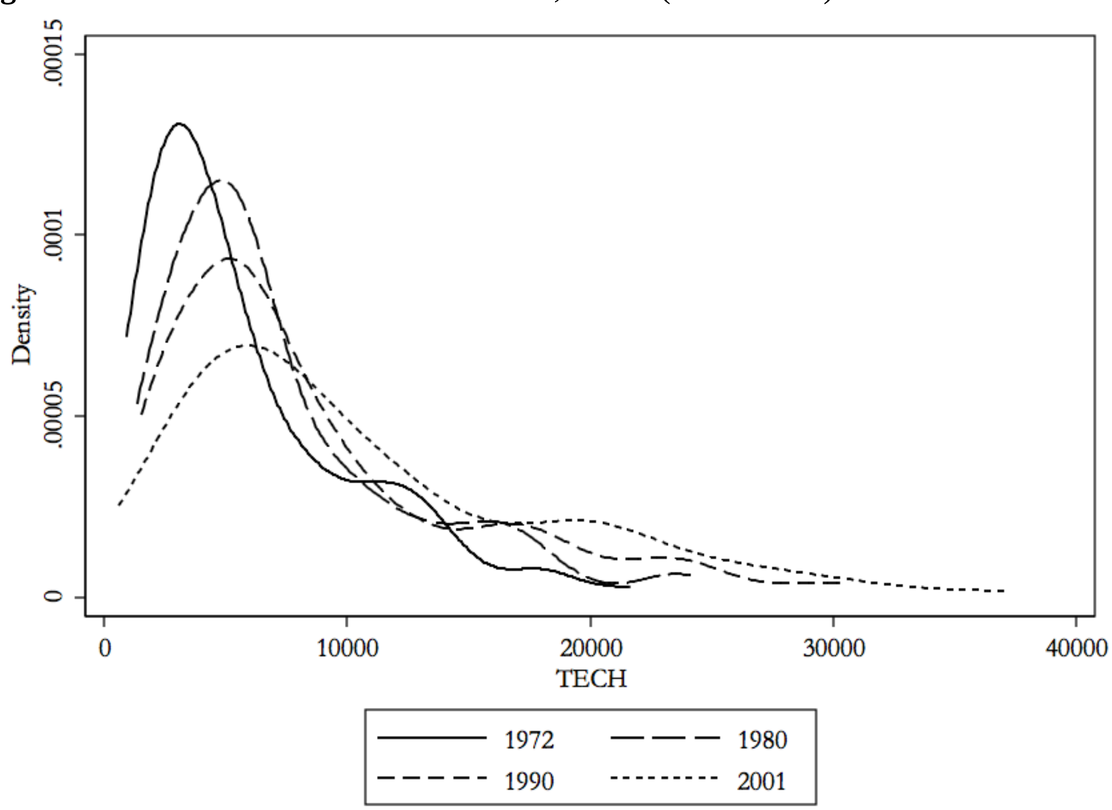
[22] It is important to remember that the countries described in this analysis do not represent a random sample. The idea is not to be able to generalize from the countries examined here to an overall population. Though not entirely complete (for example, the U.S. is notably absent, since it does not export to itself), the collection of countries is conceptually closer to the actual global population of nations.

[23] To ensure that I have not chosen anomalous years, I also generate kernel-smoothed densities using 3-year averages of *TECH* (1972-74; 1979-81; 1989-1991; 1999-01). I do not report these here since the results are almost indistinguishable.

image can help to reconcile constant inequality levels with the growing gap between the most and least sophisticated economies.

The horizontal axis of Figure 1 gauges absolute *TECH* scores, while the vertical axis describes the number of economies at a given technology level. I highlight three main results. First, the dominant peak in the distribution is found at *TECH*'s low end. By contrast, only a small number of economies appear highly sophisticated. This general imbalance holds throughout the 30-year period. Second, the positive skew evident in the distribution in 1972 has strongly and steadily increased into 2001. I interpret this to mean that there has been a significant expansion of the technological frontier, although the density of countries occupying high-sophistication positions remains low. Third, while the club of less advanced countries remains numerically dominant, its shape has been transformed. Specifically, it has shifted from a dense peak with a steep drop-off on either side to a wider and lower mode that contains countries with a more diverse range of technology levels. The decreased height suggests that membership in the club of unsophisticated economies has steadily shrunk. The increase in the peak's breadth means that there is growing heterogeneity in this peak. As well as poor economies towards the left, the mode contains middle-sophistication economies by the end of the 1990s. By 2001, Taiwan, Hong Kong, Philippines, Malaysia as well as a number of post-communist transition economies have upgraded their technological sophistication, and they approach the sophistication level of a number of OECD economies.[24]

Figure 1. Absolute densities of TECH values, n=115 (141 in 2001)



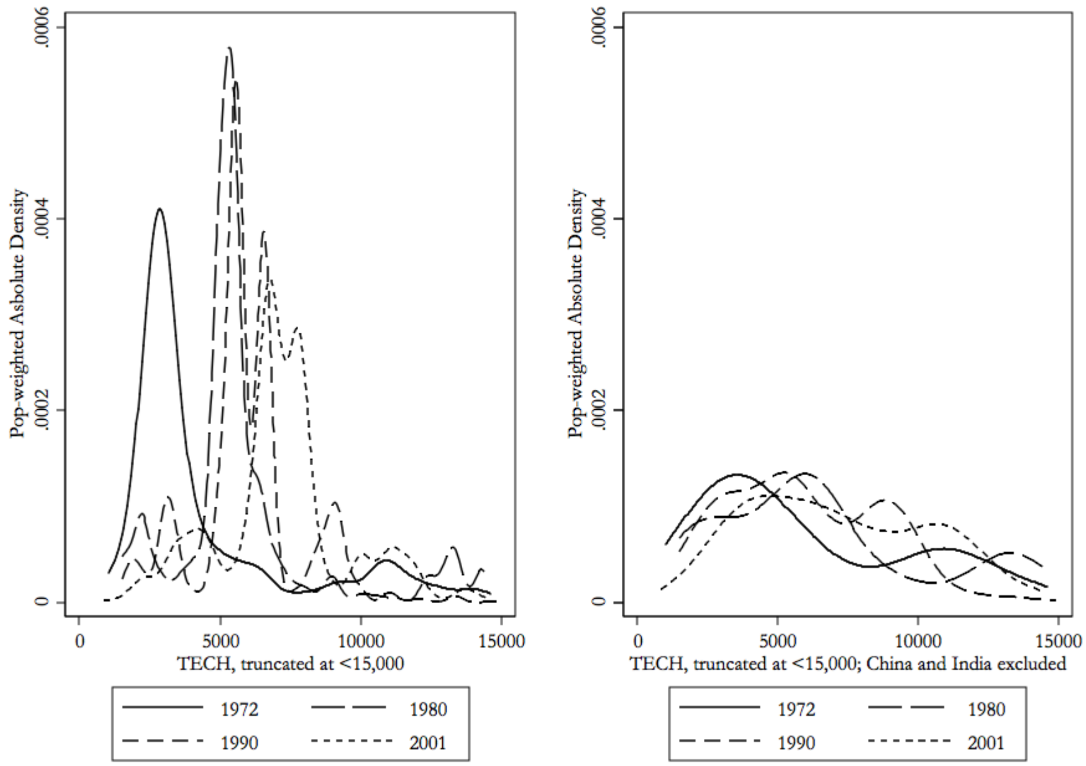
[24] The lack of service trade data may understate Hong Kong's and some other countries' true scores.

This picture is irreducible to a story of simple technological convergence or divergence. The real gap between the most and least sophisticated economies has increased over the period, mostly as a result of expansion in technological sophistication levels at the top end. This is consistent with the results shown in the upper and middle rows of Table 3. At the same time, most economies with low initial *TECH* scores have upgraded the sophistication of their exports, and the changing shape of the dominant peak provides evidence that a group of ‘middle sophistication’ countries has emerged. So Figure 1 suggests stagnation at the bottom, moderate upgrading in the middle, and rapid expansion of technology levels among technological leaders.

The statistics presented thus far treat each economy as an undifferentiated point. Figure 2 shows absolute kernel density estimates that weight each economy according to its population size. I truncate results along the horizontal axis at TECH<=15,000 to aid interpretation of the lower end, since above a threshold of 15,000 the plot generally conforms to the unweighted diagram shown in Figure 1. Figure 2 therefore focuses on the unsophisticated economies, where the bulk of the world’s population resides. The left panel of the figure shows results from all economies below the cutoff. It shows that economies housing a large proportion of the world’s population have increased their sophistication between 1972 and 2001. Moreover, the shape of the distribution changes from a single dominant mode to a ‘twin peaks’ form between 1980 and 1990. In 1972 the single peak is primarily composed of China, India, Brazil and Indonesia, who together consist of over 50% of the population of all economies for which I have data. By 1980, Brazil accelerates out of this group, and can subsequently be discerned in smaller peaks around 6,500 (1980), 9,100 (1990), and 11,000 (2001). However, the other economies remain. In 1990, the emergence of a bimodal shape is explained by India’s comparatively more rapid technological upgrading. It dominates the mode centered on 7,000, while China and Indonesia remain around their scores in 1980. This same pattern repeats in 2001.

The right panel of Figure 2 displays the same kernel density estimates but omits results from China and India. To facilitate comparison, both panels use the same scale. This figure demonstrates to what extent the changes seen on the left are explained by the development of China and India. Lacking those giant economies, whose combined population in 2001 represents 47% of the economies for which I have *TECH* data, there is evidence of a modest reduction in the most unsophisticated mode and a similarly small increase in a second, somewhat less advanced club. Technological upgrading in the context of China and India’s massive populations push forward the peak of relatively unsophisticated economies over time.

Figure 2. Population-weighted absolute densities of TECH, truncated sample



It should be cautioned that Figure 2 depends on the assumption that technology is evenly distributed within country populations. This is unlikely, especially in countries like China and India, where highly uneven income distributions hint at a wide disparity in technological advancement. Xu (2007) investigates China's technological inequality further, noting that Chinese exporting regions have per capita incomes that are between 1.3 to 4.5 times higher than the national average in 2004. Nonetheless, Figure 2 provides some sense of the effect of China and India's rise, even while it is overstated by distributional assumptions.

4b. Technology Positions Are Stable Over Time

The preceding analysis could characterize a distribution in which countries hold their relative positions over time as much as one where they switch places. Do economies that start out unsophisticated in 1972 remain so in 2001? Do technological leaders at the beginning of the period persevere at the end? More generally, do we see intradistributional stability or churning over time?

I explore this first using a random effects growth model in which I predict change in *TECH* as a function of time in years.[25] Ordinary least squares (OLS) assumptions are inapplicable here, since a each country's results across time are often serially correlated. A random effects model permits me to estimate the relationship between time and change

[25] Output shown in Appendix B. I ran the random effects specification after performing the Hausman test, which confirms the null hypothesis that both the random effects and fixed effects are consistent but random effects is efficient.

in technological sophistication, controlling for countries' different technological starting points. Using this model I find a positive, statistically significant ($p=0.000$) relationship between time in years and *TECH*. With each additional year, the model predicts an associated increase in *TECH* of 176.4 (hence 30-year growth is estimated at 5,292). This estimation approach also measures intraclass correlation, or rho: the association between observations on the same unit, as compared with observations from other economies. Rho values close to zero indicate that observations on a single country across time are no more similar to each other than cases from all other countries. Conversely, values near one indicate that cases from a single country are more similar than cases from other countries. My rho estimate of 0.83 means that countries that begin with high *TECH* scores continue to enjoy high scores over time. As well, countries with low scores persist in their low levels of technological sophistication over the 30-year period.

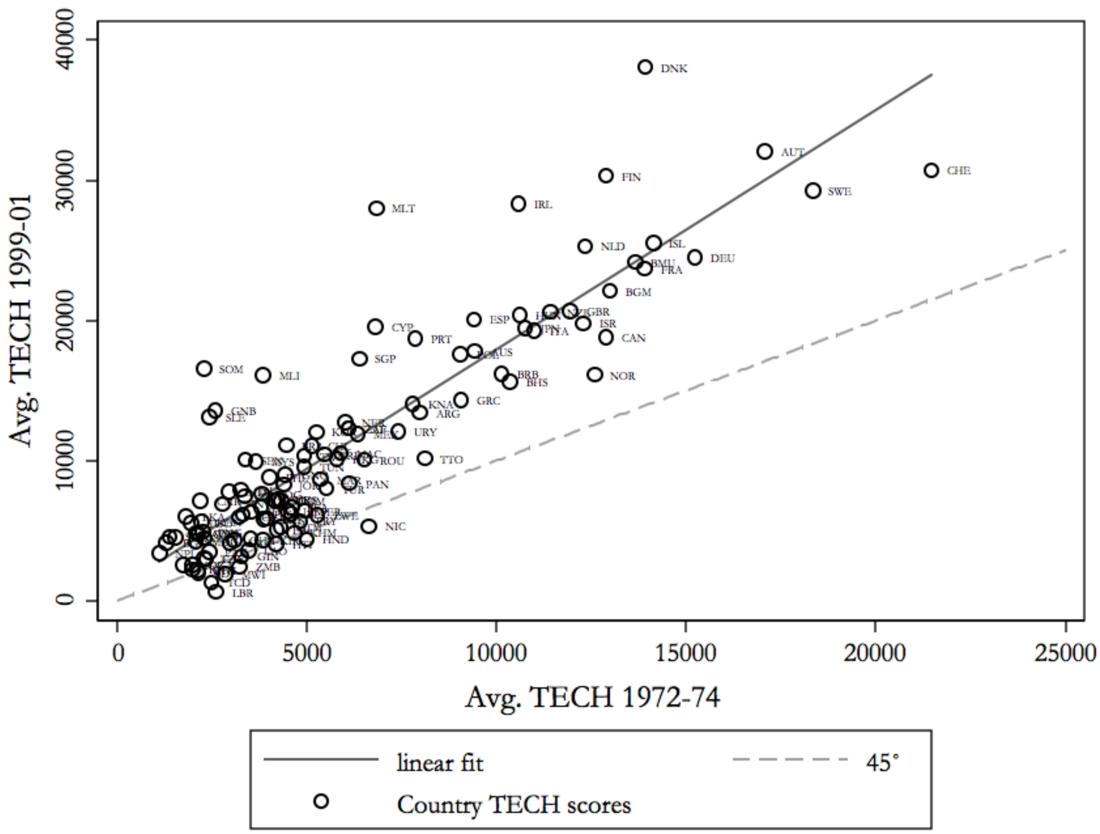
This provides general evidence in favor of temporal stability in relative technological positions, but few details. To investigate further, I plot *TECH* values from the beginning of the study period against positions at the end in Figure 3.[26] I also display two interpretative aids: a linear fit line, as well as a line at 45˚. Data points below the dashed 45˚ line have diminished their sophistication in real terms. Almost all countries remain above 45˚, which confirms the secular upward trend in levels of technological sophistication between 1972 and 2001 found in the random effects model. Only a handful of economies have suffered an absolute decrease in their technological capabilities.

The solid linear fit line predicts a relationship between starting and ending *TECH* scores using ordinary least squares. Economies directly on the linear fit line are those whose starting *TECH* score perfectly predict their technology level in 2001. Economies below the solid line have dropped down the ladder of technological sophistication relative to their peers, while those above have leapfrogged.

Figure 3 corroborates the general story of positional stability drawn from the random effects estimate. Starting and ending TECH scores are highly correlated, with a coefficient of 0.89. The strength of this relationship is clearest among countries with low and moderate initial levels of technology. These economies remain in roughly the same low and moderate positions in which they began. Above an initial TECH score of 7,000, the results are mixed. While all of these economies have grown in absolute terms, they have larger deviations from the linear estimate. Denmark, Ireland and Finland and a few others have upgraded their export sophistication at a rate notably higher than the entire distribution's linear fit. By contrast, Switzerland, Bermuda and Germany have grown more slowly than the trend. However, even if these countries have underperformed relative to the average annual growth trend, they remain among the most advanced economies in 2001.

Figure 3. 3-year Average *TECH*, 1972-74 against 1999-2001

[26] To ensure that 1972 and 2001 are not idiosyncratic years, I graph a 3-year average of 1972 to 1974, against average scores from 1999 to 2001



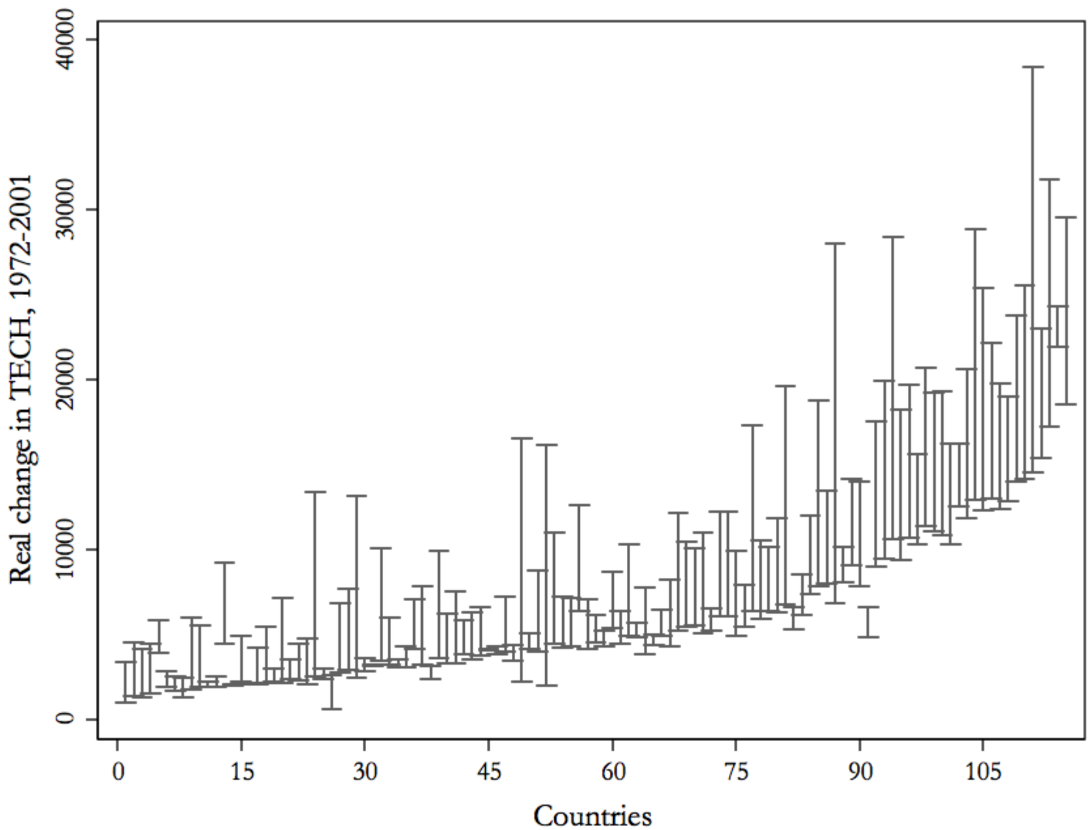
Some economies that began in 1972 at low and moderate *TECH* levels appear to have leapt forward by century's end. Among low scorers, Mali, and Somalia have increased their *TECH* scores at a substantially faster rate than the norm. In both cases however, their strong growth is an artifact of the indicator's construction, as well as being sensitive to the number of years used to create starting and ending averages for Figure 3. Mali, for example has shifted from a revealed comparative advantage in 'Food and live animals chiefly for food' (Class 0, 1-digit SITC) in 1972, to a focus in 2001 on "Miscellaneous manufacturing" (class 8) and "Machinery and transport equipment" (Class 7). Yet it's apparent leap forward in Figure 3, like Somalia's is more a function of its small export basket being dominated by a few goods, which in selected years enjoy surprisingly high comparative unit prices.[27] Among larger economies, this effect, possibly a function of data entry error would be filtered out, but in these small economies it is magnified.

Among moderate initial *TECH* scores, Singapore, Malta, Cyprus and Ireland have outperformed their peers. Malta's score appears to be largely due to their small economy's emergent specialization in electronic integrated circuits, sold at a price premium, and occupying close to half of its U.S. exports at century's end. Ireland and

[27] For example, 42% of Mali's export basket in 2001 are of wheeled toys with a *Q* near 1, while in 1999 this good occupies only 1.5% of total exports while being sold at a *Q* value of almost 40. This dramatic compositional shift is partly a function of undiversified exports. One wonders whether or not this case is also exacerbated by the use of U.S. import data rather than total Malian exports to the world.

Singapore however appear to reflect more diversified shifts towards high sophistication. 75% of Singapore's U.S. exports are focused on various kinds of machinery and transport equipment throughout the 30-year period. It's focus shifts however, from cathode ray tubes, photocells, radio broadcast receivers, diodes and transistors in 1972, to hard disk drives and other computer components by 2001, the latter composing part of a highly diversified export basket consisting of almost 2400 distinct goods.

Figure 4. Real change in TECH, balanced panel



It appears that some of the cases described above are instances of switching successfully from one 'category' of sophistication to another. As Figure 3 demonstrates, this phenomenon is not widespread. But some mobility patterns are evident in the distribution. Economies above initial TECH of 7,000 have fairly consistently grown faster than the linear estimate. Figure 4 makes this point clearly, by plotting starting and end TECH scores for all countries for which I have complete 30-year results. There is a strong relationship between initial *TECH* levels and subsequent growth. A few lower *TECH* economies have made large gains, and some higher-*TECH* economies have upgraded their sophistication less quickly, but the general trend is towards reinforcing the position of initial technological leaders.

4c. Winners win by producing the same goods better, and more intensively

Determining the precise nature of shifts in an economy's *TECH* score remains difficult because it is a function of as many as 15,000 different products it may export at any given moment. Moreover, each good's contribution to *TECH* depends on its relative quality, implied productivity, and its share of total exports, each also changing from one year to the next. Despite this challenge, we want to know why the initially technologically advanced economies appear to be those that have most significantly upgraded their sophistication between 1972 and 2001. Have they, for example, engaged in systematic quality upgrading, or have they grown as a function of adding new products to their repertoires? Moreover, have these high-performing economies increased the sophistication of their exports in a coherent way, or are their upgrading experiences idiosyncratic? Among late-industrializing economies we might want to know why Singapore and Ireland have performed particularly well, while others continue to lag behind – including some like Hong Kong whose per capita GDP has grown dramatically over the period studied.

To answer these questions, I unpack year-on-year changes in *TECH* into distinct contributions from changes in quality and greater implied productivity, in export shares, and from the addition of new products and the elimination of old ones. I adapt a method proposed by Foster et al (1998) to capture these distinct shifts, such that the change in *TECH* in a given country *n* between years *t-1* and *t* be given by :[28]

$$\Delta TECH_{nt} = \sum_{g\in C} x_{t-1} p_t \Delta q_t + \sum_{g\in C} x_{t-1} q_{t-1} \Delta p_t + \sum_{g\in C} \left(pq_{t-1} - TECH_{t-1}\right)\Delta x_t + \sum_{g\in C} p_t \Delta q_t \Delta x_t + \sum_{g\in C} q_{t-1} \Delta p_t \Delta x_t + \sum_{g\in E} x_t \left(pq_t - TECH_{t-1}\right) - \sum_{g\in L} x_{t-1}\left(pq_{t-1} - TECH_{t-1}\right)$$

The first two terms consider 'within-product' effects. The first term captures overall contribution from quality upgrading (***q***), holding all else constant, for products an economy continues to export in adjacent paired years ($g \in C$). The second term measures adjacent-year changes in *TECH* that are due to changes in the implied productivity (***p***) of products an economy exports, all else equal. Third comes the 'between-product' component, which quantifies the contribution of changes in export basket composition among consistently exported goods. The next two terms are covariance or cross terms that permit the separation of between- and within- (***q*** and ***p***) effects.[29] The fourth term measures the covariance of implied productivity and export share, holding quality constant. The fifth describes the covariance of quality and export share, holding implied productivity constant. Sixth, the 'product-entry' component measures the impact on *TECH* as an economy adds new goods that it did not export in an earlier year, holding all

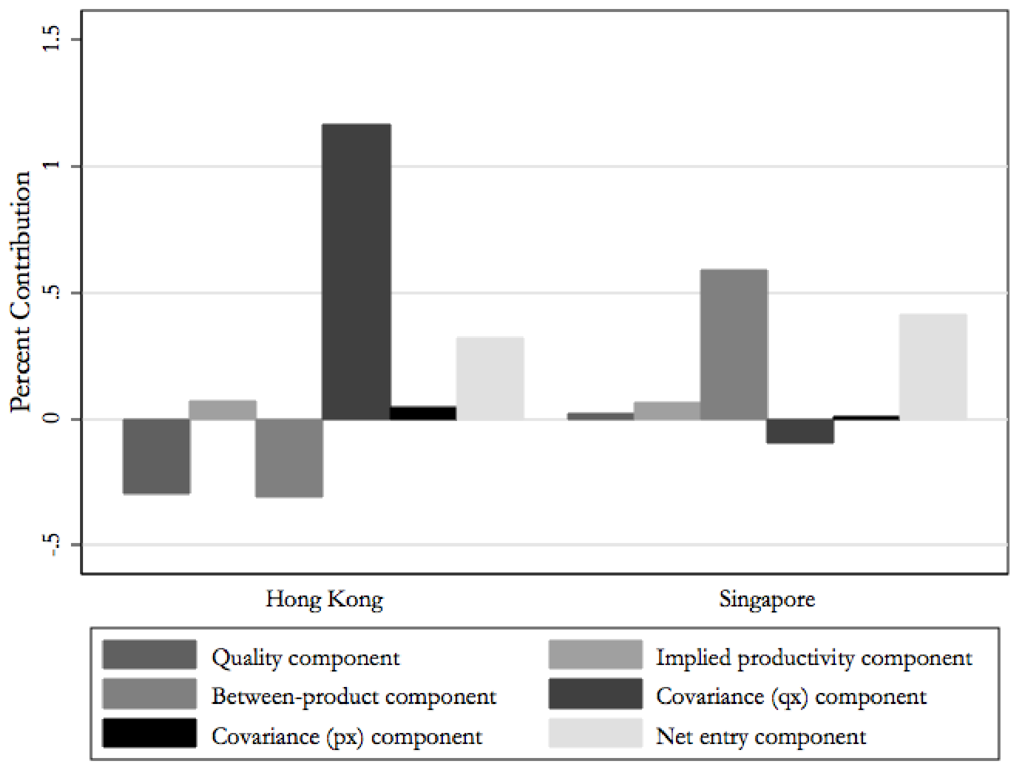
[28] Foster et al (1998) review literature that seeks to measure productivity differences among plants in the same industry. Hence, the authors decompose a given industry's productivity level into contributions as individual plants become more or less productive, as well a contributions as plants occupy varying market shares. In the case of *TECH*, we need a second-order decomposition: not only between changes in export shares and product characteristics, but also between implied sophistication and quality, within individual product values.

[29] In earlier iterations, I decomposed changes in *TECH* using between and within terms that held the other constant using averages across periods. While this eliminates the covariance term, the within-component still contains some impact from export reallocation, and vice versa.

else equal.[30] Last, the 'product-exit' component explains the effect on *TECH* as an economy stops exporting goods that it exported in an earlier year, again holding all else equal.[31]

The between-product, exit and entry terms include deviations of individual country/product sophistication (***pq***) from the overall country *TECH* score. For the between-product term, this means a shift in export share will contribute positively only when the goods towards which the economy is being shifted have an above-average level of implied productivity. Similarly, a product's entry or exit drives a change in *TECH* only insofar as the goods added or subtracted diverge from the country's initial level of sophistication.

Table 5. Components of Growth (1972-2001) in *TECH*, Hong Kong and Singapore



I decompose annual changes in each country's *TECH* between 1972 and 2001. Since the U.S. import data switches from the TSUSA to the HS product coding systems in 1989, I cannot account for changes between 1988 and 1989. To begin exploring these decompositions, I compare percentage contributions from the components of growth in TECH from Singapore and Hong Kong in Figure 5. Both are Asian 'Tigers' that experienced rapid income growth over the period studied. The decision to examine these countries is also guided by the fact that Singapore is among the fastest-upgrading economies, with an average annual growth in *TECH* of 332.3 as compared with a 'world'

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[30] *E* is the set of goods that an economy exports in *t* but not *t-1*.

[31] *L* is the set of goods that an economy exports in *t-1* but not *t*

average of 201.3, while Hong Kong's annual growth is below average, registering only 147.4.

Figure 5 reveals notable differences in each economy's upgrading pattern. Hong Kong appears to have decreased its quality levels, while slightly shifting its attention to goods with higher implied productivity. It also displays a strong positive contribution from the covariance term between quality and export share. That is, the goods for which Hong Kong has performed quality upgrading, it has also exported more intensively.

For Singapore, between-product and net entry components dominate. Singapore has increased its *TECH* score by changing the composition of exports towards goods that it produces in higher quality, or which have greater implied productivity. It has also undergone notable structural change towards new goods that enhance the overall sophistication of its export basket.

To get a clearer sense of the regularities in technological upgrading, I create 4 country groups on the basis *TECH* scores in 1972. Countries in the most advanced group have initial *TECH* scores above twice the mean score in that year. The upper-middle group consists of countries with initial *TECH* scores greater than or equal to the mean and less than twice the mean. Economies in the lower-middle group have *TECH* scores below the mean and above half the mean. Those in the least advanced group have starting *TECH* scores below half the 1972 mean. These groups were chosen since they broadly conform to components of the kernel density plots, in particular separating the high-performing economies as a distinct group.[32] To ensure that these groups are significantly different from each other, I perform a one-way analysis of variance (ANOVA) using countries' 28-year average $\Delta TECH$. The test reveals that the groups have significantly different mean changes in *TECH*, with an associated p-value=0.000.

Table 4 shows each group's percentage contributions from each decomposed component, with a single net entry term that summarizes the effect of both entry and entry. It also displays means for the average change in *TECH* for each group. Entries in the table represent 28-year averages, since I cannot account for changes between 1971 and 1972, or between 1988 and 1989. I present results from a balanced panel to ensure that country-group contributions equal each group's average $\Delta TECH$.

The bottom row of Table 4 confirms that those economies that start off with high TECH scores in 1972 have, on average, grown the most over the subsequent 30-year period. Average growth in TECH diminishes systematically with a disadvantaged starting point. Moreover, the initially advanced group has grown in common ways. Among consistently exported goods, they show large contributions from quality upgrading, from increases in the implied productivity, and from increasing their focus on more advanced goods. By contrast, their contribution from net entry is small. The trend as we move to less initially-sophisticated countries moves in the opposite direction. Less-sophisticated economies have a greater contribution from the addition of more sophisticated goods that they did not produce in the past. They only engage in limited quality upgrading within goods, and somewhat more from the export of goods whose implied productivity has risen.

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[32] Results using groups formed from initial-*TECH* quartiles did not importantly differ but were less preferable for substantive reasons. To see a kernel density plot with the groups explicitly marked, see Table B5 in the appendix.

Table 4. Decomposition of *TECH* into percentage contributions from within, between, covariance, and net entry components for initial TECH groups

	Initial *TECH* Groups			
	High (n=15)	Upper Middle (n=25)	Lower Middle (n=39)	Low (n=31)
Quality	32%	42%	8%	10%
Implied productivity	37%	31%	33%	29%
Between-product¯	102%	111%	44%	-4%
Covariance ΔqΔx	-85%	-110%	-40%	-3%
Covariance ΔpΔx	7%	-5%	-13%	-24%
Net Entry	6%	30%	68%	92%
$\overline{\Delta TECH}$	364.98	244.04	106.03	107.13

5. Conclusion

My results show that technology gaps have not shrunk in the age of globalization. By constructing an index that measures an economy's technological sophistication as a function of the products it exports, as well as the quality levels of those goods relative to competing exporters, I have traced complex patterns in international technology gaps between 1972 and 2001. I provide evidence that while some less advanced economies have upgraded their technology levels during this period, it is the most advanced economies that have built on their initial lead at a faster rate, and they have done so in similar ways. Overall, I provide some initial confirmation that specialization in high-sophistication goods spurs a circular and cumulative technological advantage that outweighs the increasing facility of codified information transmission as a means of technological diffusion. In future work I seek to further investigate this hypothesis.

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Data Appendix

Table A1. Exporting countries in *TECH*

Country	CODE	Country	CODE	Country	CODE	Country	CODE	Country	CODE
AFGHAN	AFG	COS_RICA	CRI	ICELAND	ISL	MONGOLA	MNG	SRI_LKA	LKA
ALBANIA	ALB	CROATIA	HRV	INDIA	IND	MOROCCO	MAR	ST_K_NEV	KNA
ANGOLA	AGO	CYPRUS	CYP	INDONES	IDN	MOZAMBQ	MOZ	SUDAN	SDN
ARGENT	ARG	CZECHO	CZK	IRELAND	IRL	MRITIUS	MUS	SURINAM	SUR

ARMENIA	ARM	CZECHREP	CZE	ISRAEL	ISR	NEPAL	NPL	SWEDEN	SWE
AUSTRAL	AUS	C_AFRICA	CAF	ITALY	ITA	NETHLDS	NLD	SWITZLD	CHE
AUSTRIA	AUT	DENMARK	DNK	IVY_CST	CIV	NEW_GUIN	PNG	S_AFRICA	ZAF
AZERBAIJ	AZE	DJIBOUTI	DJI	JAMAICA	JAM	NEW_ZEAL	NZL	TAIWAN	TWN
BAHAMAS	BHS	DOM_REP	DOM	JAPAN	JPN	NICARAGA	NIC	TAJIKIST	TJK
BARBADO	BRB	ECUADOR	ECU	JORDON	JOR	NIGER	NER	TANZANIA	TZA
BELARUS	BLR	EGYPT	EGY	KAZAKHST	KAZ	NORWAY	NOR	THAILAND	THA
BELIZE	BLZ	EQ_GNEA	GNQ	KENYA	KEN	PAKISTAN	PAK	TOGO	TGO
BEL_LUX	BGM	ESTONIA	EST	KIRIBATI	KIR	PANAMA	PAN	TRINIDAD	TTO
BENIN	BEN	ETHIOPIA	ETH	KOREA_S	KOR	PARAGUA	PRY	TUNISIA	TUN
BERMUDA	BMU	FIJI	FJI	KYRGYZST	KGZ	PERU	PER	TURKEY	TUR
BNGLDSH	BGD	FINLAND	FIN	LAO	LAO	PHIL	PHL	TURKMENI	TKM
BOLIVIA	BOL	FRANCE	FRA	LATVIA	LVA	POLAND	POL	UGANDA	UGA
BOSNIA-H	BIH	GAMBIA	GMB	LEBANON	LBN	PORTUGAL	PRT	UKINGDOM	GBR
BRAZIL	BRA	GEORGIA	GEO	LIBERIA	LBR	ROMANIA	ROU	UKRAINE	UKR
BULGARIA	BGR	GERMAN	DEU	LITHUANI	LTU	RUSSIA	RUS	URUGUAY	URY
BURKINA	BFA	GHANA	GHA	MACAU	MAC	RWANDA	RWA	UZBEKIST	UZB
BURUNDI	BDI	GREECE	GRC	MACEDONI	MKD	SALVADR	SLV	VIETNAM	VNM
CAMBOD	KHM	GUATMALA	GTM	MADAGAS	MDG	SAMOA	WSM	ZAIRE	ZAI
CAMEROON	CMR	GUINEA	GIN	MALAWI	MWI	SENEGAL	SEN	ZAMBIA	ZMB
CANADA	CAN	GUYANA	GUY	MALAYSIA	MYS	SIER_LN	SLE	ZIMBABWE	ZWE
CHAD	TCD	G_BISAU	GNB	MALI	MLI	SINGAPR	SGP		
CHILE	CHL	HAITI	HTI	MALTA	MLT	SLOVAKIA	SVK		
CHINA	CHN	HONDURA	HND	MAURITN	MRT	SLOVENIA	SVN		
COLOMBIA	COL	HONGKONG	HKG	MEXICO	MEX	SOMALIA	SOM		
CONGO	COG	HUNGARY	HUN	MOLDOVA	MDA	SPAIN	ESP		

Figure A2. Scatterplots of U.S. Import and WTF-derived *EXPY* scores, selected years

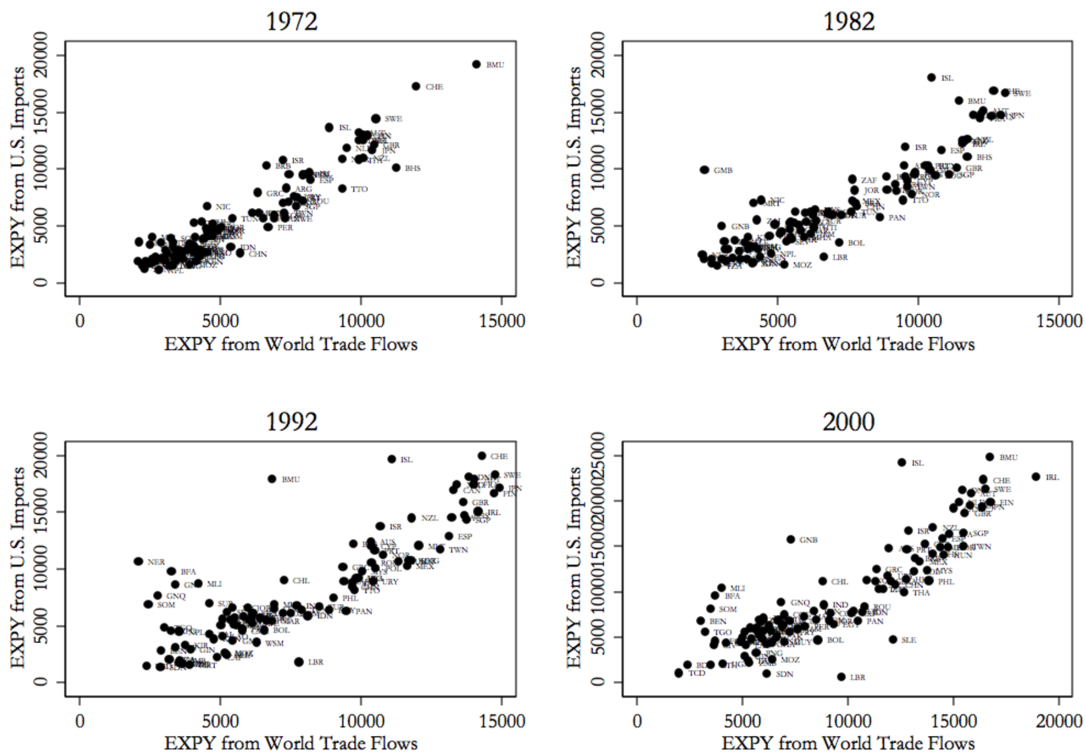


Table A2. Distribution of unadjusted and adjusted *Q* scores

	Unadjusted *Q*		Adjusted *Q*	
	(1)	(2)	(3)	(4)
	Percentiles	Smallest 5	Percentiles	Smallest 5
1%	**0.013**	**1.00E-07**	**0.0333766**	**4.97E-04**
5%	0.103	1.07E-07	0.136158	5.31E-04
10%	0.229	1.31E-07	0.2678799	6.95E-04
25%	0.588	1.83E-07	0.628105	7.75E-04
50%	1.000		1.000	
		Largest 5		Largest 5
75%	1.599	34468.98	1.563246	767.838
90%	4.106	35220.6	3.82981	878.9839
95%	8.256	39357.46	7.090668	928.3124
99%	**51.180**	**47545.69**	**24.29749**	**1040.111**

Figure B1. *TECH* and TFP in 1988

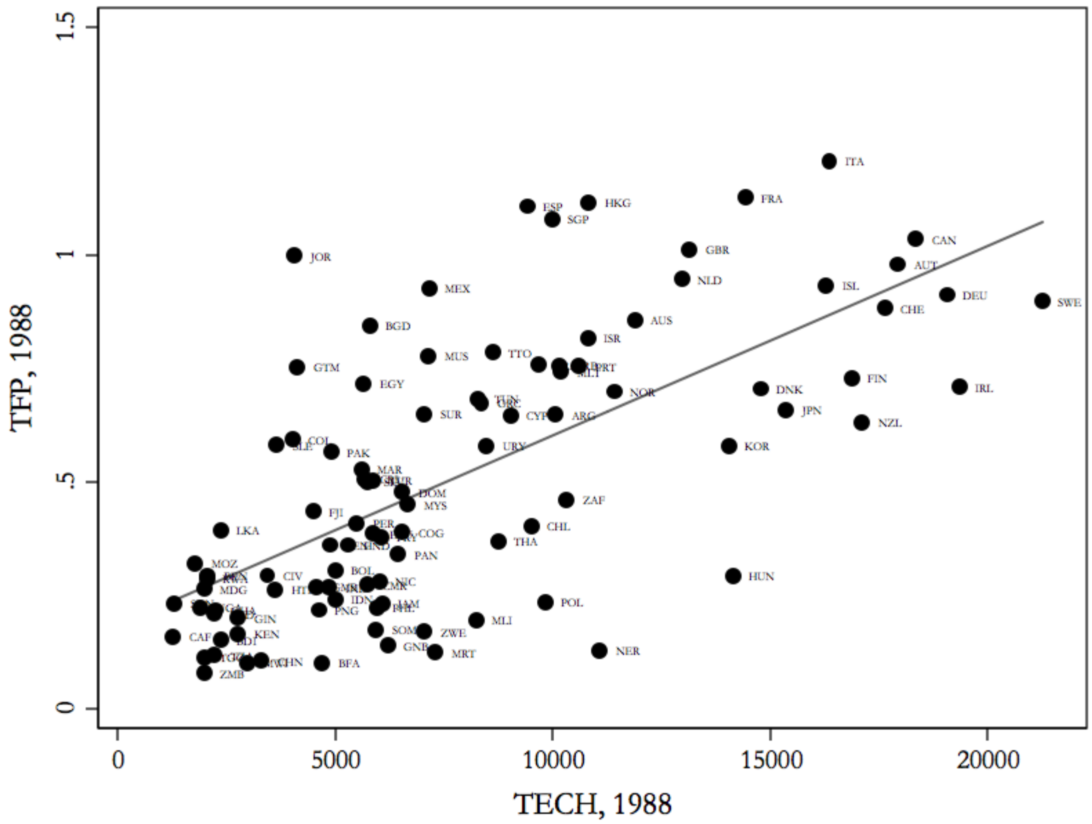
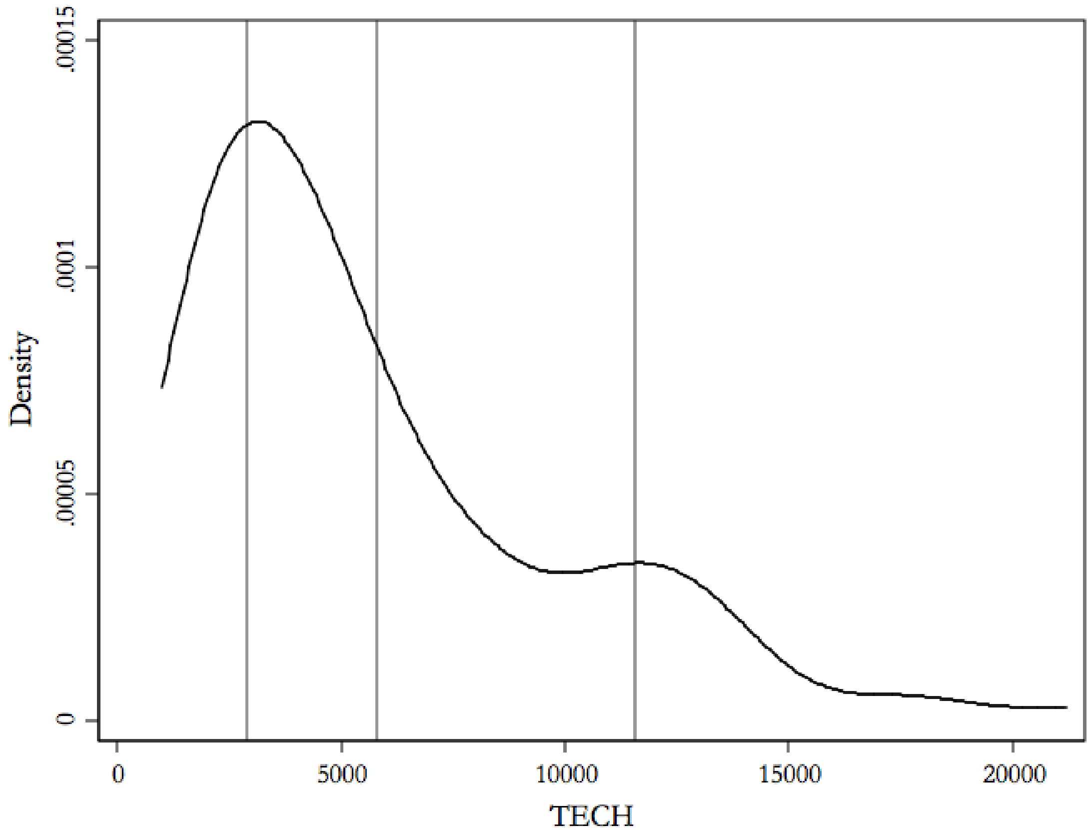


Table B1. Determinants of growth in *TECH*, Random effects estimate (standard errors in parentheses)

Variable	Coefficient
Constant	176.36
	(0.000)
Year	-342340.7
	(0.000)
σ_u	5420.43
σ_e	2458.42
ρ	.829

Figure B2. 1972 Kernel Density Plot with TECH Decomposition Groups


Density
.00015
.0001
.00005
0
0
5000
10000
15000
20000
TECH